J. Innovative Eng. Nat. Sci., vol. 4, no. 1, pp. 138-146, 2024.
http://doi.org/10.61112/jiens.1365282

Journal of Innovative Engineering and Natural Science
(Yenilikçi Mühendislik ve Doğa Bilimleri Dergisi)
journal homepage: https://jiens.org

Original Paper

Path planning of autonomous mobile robots based on Voronoi diagram and ant colony optimization

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ARTICLE INFO

Article history:
Received 23 Sep 2023
Received in revised form 17 Nov 2023
Accepted 22 Dec 2023

Available online

Keywords:
Path Planning
Voronoi diagram
Ant colony optimization
Autonomous mobile robot

ABSTRACT

Path planning aims to enable autonomous robots to navigate safely and efficiently from a starting point to a target point in challenging and dynamic environments. Path planning in robotics is highly significant and still an ongoing subject of research. The increasing use of robots in various applications such as industrial automation, service robotics, and autonomous vehicles has brought forth the need for reliable and efficient path planning algorithms. The inherent capability of Voronoi diagrams to partition space based on proximity makes them an effective framework for research in path planning. Ant colony optimization, a bio-inspired optimization technique, is based on the foraging behavior of ants and is commonly employed to address the traveling salesman problem and various other combinatorial optimization problems. A hybrid method was adopted in this study by combining a Voronoi diagram and an ant colony algorithm. To create paths for the robot where it can stay as far away from obstacles as possible, a Voronoi diagram was utilized. Additionally, to find the shortest path from the starting point to the destination among these paths, ant colony optimization was employed. The main contribution of the study lies in the combination of the Voronoi diagram for obstacle avoidance and ant colony optimization for finding the optimal path. The combination of these techniques makes an effective contribution to robotic path planning by focusing on ensuring safety by avoiding obstacles while optimizing the shortest path. Experimental studies show that the hybrid method produces successful results for the desired purpose.

I. INTRODUCTION

An important component of autonomous navigation for mobile robots is the planning of a safe and convenient path from a starting point to a target point avoiding obstacles. For path planning, algorithms need to be designed to find the path from the current location of the robots to the destination point they want to go to. While designing the algorithms, information such as sensor data that enables the robot to receive information from the outside world and a map of the environment in which the robot is located are used. Path planning is usually analyzed in two main categories: global path planning and local path planning. Global path planning usually involves the creation of a map and aims to determine the general route from the robot's current location to the target. Local path planning, on the other hand, has the function of correcting and optimizing this global route using instantaneous environmental information. Since mobile robots play important roles in many areas ranging from defense to logistics, health to agriculture, studies on the development of autonomous path planning capabilities are still ongoing. In this context, the development of autonomous path planning systems aims to increase the capacity of mobile robots to adapt to the various challenges and variables they face. Advances in sensor technologies enable mobile robots to perceive their environment more precisely, allowing path planning algorithms to be more effective in complex environments.

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In the literature, there are a number of developed algorithms for path planning of mobile robots. Traditional algorithms such as Dijkstra [1], A* [2] and Probabilistic Road Maps (PRM) [3] are the most fundamental algorithms used in path planning and are still used in certain studies. Additionally, algorithms such as Rapidly-Exploring Random Trees (RRT) [4] and its variants have enabled successful outcomes in path planning for high-dimensional and continuous state spaces. These algorithms excel in environments where information about the surroundings is available and computational cost is not a significant constraint. However, in large-scale or real-time scenarios, these algorithms can become computationally expensive. Heuristic algorithms, which are used as an alternative to traditional algorithms, can obtain effective results in a shorter time in larger and more complex search areas, usually by using heuristic information and working with population-based methods.

Heuristic algorithms also, such as Genetic Algorithms [5], Ant Colony Optimization (ACO) [6], Particle Swarm Optimization (PSO) [7], and Artificial Bee Colony (ABC) [8] have shown promising results in path planning, enhancing navigation performance. GA models the process of natural selection, ACO is inspired by the foraging behaviour of ants, PSO effectively explores search spaces by modelling the social behaviour of particles, and ABC simulates the foraging behaviour of honeybees. These heuristic approaches provide robust and adaptable solutions for challenging path planning problems across many domains. Despite advances in path planning for mobile robots, several challenges remain. Among these challenges, uncertainty and collision avoidance in dynamic environments remains an active area of research. The development of efficient and safe path planning algorithms plays an important role in unlocking the full potential of autonomous mobile robots in different applications and contributing to safer interactions between robots and their environments. Path planning has a bright future as robotics technology advances, including cutting-edge techniques like swarm intelligence and heuristic algorithms, and has a lot of potential to provide safe and effective navigation in challenging real-world situations. Besides, various strategies to mitigate these challenges, such as hybrid methods combining multiple algorithms, are also discussed in the literature.

One fundamental concept in path planning for mobile robots is the representation of the environment. Various techniques, such as occupancy grids, potential fields, and Voronoi diagrams, are employed to model the surroundings and create a digital map. These representations serve as the foundation for generating feasible paths while considering obstacles, restricted areas, and mission objectives. The choice of representation heavily influences the efficiency and accuracy of the path planning process. In this study, a hybrid approach was aimed by combining a Voronoi diagram and an ACO. Unlike grid-based mapping, the robot's continuous environment path planning was performed. Using the Voronoi diagram, paths that the robot can traverse were generated at a distance from obstacles whenever possible, thus minimizing the robot's contact with obstacles and ensuring a safe path planning. Although paths passing through adjacent obstacles were automatically generated by Voronoi, they were ignored and not used in the path planning. Then, the shortest path among all the paths obtained through Voronoi was determined using ACO.

The main contributions of the study are as follows:

- By using Voronoi diagrams, safe paths away from obstacles are created for robots. Thus, the risk of hitting obstacles during the movement of the robot is minimized.

- Thanks to the paths created with Voronoi, the need to control all cells in a cell-based environment is eliminated. Thus, the possible paths for the ant colony optimization are reduced and the computational cost is reduced.

The rest of the paper is organized as follows: the related studies, including both Voronoi diagrams and ACO were given in section 2. Section 3 presents material and methods. Experimental studies were presented in Section 4, and the Conclusions were presented in section 5.

II. RELATED STUDIES

Using Voronoi diagrams for path planning is a topic of interest in the field of robotics. There are many studies in the literature that utilize Voronoi diagrams to generate optimal or near-optimal paths for mobile robots. Candeloro et al. [9] introduced a rapid and dynamic path-planning system for 3-DOF marine surface vessels, particularly in shared environments with other marine vehicles. The method employs Voronoi diagrams to generate initial paths that consider clearance constraints, including land and shallow waters. Wei et al. [10] proposed a novel path planning algorithm based on Centroidal Voronoi Tessellation (CVT) for self-assembly of swarm robots. The algorithm enables swarm robots to autonomously move from initial virtual regions to target virtual regions using a collaborative scheduling approach. Combining Voronoi diagrams with the A* algorithm for path planning has also been presented in the literature [11, 12]. In addition to the A* algorithm, there is also a study in which safe path planning is achieved by combining the Voronoi diagram with the D* algorithm [13]. In another study [14] using Voronoi diagram and RRT as a hybrid, to improve RRT motion planning effectiveness, presented a heuristic path planning approach based on the Generalized Voronoi Diagram (GVD). These studies demonstrate the versatility of Voronoi-based path planning algorithms for autonomous navigation. Researchers are continually looking into and developing new techniques and advancements to increase the efficacy and applicability of Voronoi-based path planning to actual situations.

There are also path planning studies that employ ACO [6, 15]. In both of these studies, a grid-based approach was utilized. However, in this particular case, the algorithm considers all grids when planning the path. There are also studies in which improvements have been made in the ACO to achieve better performance in path planning. Some studies propose to overcome the shortcomings of traditional ACO for solving path planning problems. Liu et al. [16] proposed firstly an adaptive pheromone concentration setting to improve guidance and prevent excessive deviation in the early stages. Secondly, they proposed a novel heuristic mechanism with directional judgment to enhance search efficiency and the smoothness of the planned path. Wu et al. [17] proposed firstly, it incorporates a new heuristic mechanism with orientation information to guide the algorithm more effectively, improving convergence speed. Secondly, an enhanced heuristic function is introduced to optimize path planning. Lastly, a method for unevenly distributing initial pheromone concentration is proposed to prevent blind searching. Miao et al. [6] introduces an improved adaptive ant colony algorithm (IAACO) to address the limitations of the traditional ACO in indoor mobile robot path planning. In another study proposed by Zong et al. [18], the traditional ACO was combined with GA and thus it was stated that the developed algorithm converged faster.

In this study, the computation cost has been reduced by performing path planning solely through the paths identified by the Voronoi diagram, without the need to examine all grids in the workspace. In addition, safe path planning is aimed at ensuring that the paths on which the robot will move are as far away from obstacles as possible, thanks to the Voronoi diagram. This approach provides a safer path by reducing the potential risks around the robot. Furthermore, it is known that heuristic approaches used in path planning can generate solutions more quickly compared to traditional methods and have lower computational costs. Due to these characteristics, the utilization of ant colony optimization, one of the heuristic approaches, in path planning along with Voronoi diagrams has played a significant role not only in finding the most suitable path but also in further reducing computation costs.

III. MATERIALS AND METHODS

3.1 Voronoi Diagrams

The Voronoi diagram is a powerful geometric tool that partitions the geometric space in a manner that ensures the boundaries of the regions are as far away as possible from all obstacles in the crowded environment [19]. Voronoi diagrams, with their inherent capability to partition space based on proximity, offer a robust framework for path planning studies [9]. Voronoi diagrams excel in path planning by virtue of their boundary characteristics. They are a geometric concept that is mathematically easy to calculate and implement. Therefore, it can be preferred in robotic applications that require fast calculations in real-time systems. The Voronoi cell boundaries constitute optimal routes for path planning purposes. These boundaries serve as navigational paths that maximize distances from obstacles, making them ideal for route optimization and collision avoidance. The Voronoi diagram consists of lines equidistant from points. An example Voronoi diagram for 8 points is shown in Figure 1.

Given a set of points $P = \{P_1, P_2, \cdots, P_n\}$, on the plane $\mathbb{R}^2$, the Voronoi region of the point P_i is the set of points, which is given in Eq. 1.

$$V_i = \{P \in \mathbb{R}^2 | \; d(P, P_i) \leq d(P, P_j) \; \forall j \neq i\} \tag{1}$$

where, d denotes the Euclidean distance.

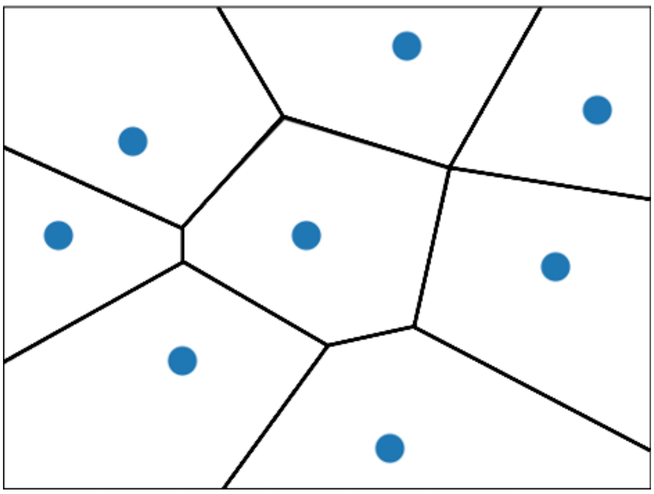

Figure 1. Voronoi diagram example for 8 points

3.2 Ant Colony Optimization

ACO is a bio-inspired meta-heuristic optimization algorithm based on the foraging behavior of ants [20]. Its inspiration from the collective intelligence behavior of real ants renders it an effective approach for a wide range of optimization problems. ACO is commonly utilized to solve combinatorial optimization problems, such as the traveling salesman problem (TSP) or the vehicle routing problem (VRP), as well as for path planning. The algorithm mimics the way real ants search for the shortest path between their nest and a food source, communicating by leaving pheromone trails on the routes they traverse. The strength of the pheromone trail is directly proportional to the path's quality; in other words, the shorter the path, the stronger the pheromone trail. As more ants follow the same path, the pheromone trail becomes more concentrated, making it increasingly likely for other ants to favor it.

In the ACO algorithm for path planning, a colony of artificial ants is generated to study different paths. Each ant builds a solution by probabilistically choosing the next step based on a combination of pheromone information and heuristic information, which represents the desirability of the next step. Heuristic knowledge is often derived from problem-specific information in the TSP, such as the distance between cities. As the ants complete their rounds, their pheromone trails are updated according to the quality of the solutions found. Better solutions contribute more to the pheromone trails and poorer solutions are lost due to evaporation. This process of pheromone updating, and evaporation allows to effectively guide the search process towards better solutions. ACO works iteratively and after several iterations, it is expected to converge towards an optimal or near-optimal solution. The key advantage of ACO is its ability to handle complex, large-scale problems, as well as its robustness to changes in problem instances. It is a powerful algorithm for path planning, especially for optimization problems where finding the optimal solution through exhaustive search is computationally infeasible. However, ACO may require fine-tuning of parameters and can be computationally intensive for large problem sizes.

The process steps of the ACO are briefly as follows: an artificial ant population is initialized to represent potential paths from a start to a target location. Pheromone values are initially assigned equally to all possible paths. The algorithm operates through iterations until a termination condition is met (e.g., a fixed number of iterations or a convergence criterion). During each iteration, ants explore the space guided by both the amount of pheromone and a heuristic function, which provides problem-specific knowledge. Eq. 2 [20] represents the probability of ant *k* moving from point *i* to point *j*.

$$P_{i,j}^{k} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{m\in N_i^k}[\tau_{im}]^{\alpha}[\eta_{im}]^{\beta}}, & if\ j \in N_i^k \\ 0, & otherwise \end{cases} \tag{2}$$

where τ_{ij} is the amount of pheromone between *i* and *j*, η_{ij} is $1/d_{ij}$, where d_{ij} is the distance between *i* and *j*. N_i^k corresponds the neighborhood of ant *k* in node *i*. α and β are parameters that control the relative relevance of two factors when an ant chooses which path to follow while looking for a solution. α represents how important a pheromone trail is to an ant's decision-making process. When the α value is higher, ants are more likely to focus on using the information in the pheromone trail when making decisions. β denotes the importance of heuristic information in an ant's decision-making process. A higher β value gives the heuristic information more weight, encouraging ants to explore potential paths based on the problem's structure.

After ants complete their tours, pheromone levels on paths are updated, favoring better paths. All the paths traversed have a certain amount of pheromone added to them. However, just like in the real world where the pheromones released by ants evaporate over time, the algorithm gradually evaporates the amount of pheromone as well. Pheromone updating is given in Eq. 3 and 4.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t+1) \tag{3}$$

$$\Delta\tau_{ij}^{k}(t+1) = \begin{cases} \dfrac{1}{L^k(t+1)}, & if\ k\ ant\ used\ path\ \ ij \\ 0 \quad , & otherwise \end{cases} \tag{4}$$

where, $\rho \in [0,1]$ is the evaporation coefficient, $\Delta\tau_{ij}$ is the pheromone update amount, m is the number of ants, and L is the path distance between i and j.

Finally, the best path among the solutions found by the ants is selected when the algorithm terminates, typically representing the shortest or optimal solution. Ants are known for their collective intelligence and ability to find the most effective solution through their interactions, using a natural optimization process as they explore the path around their environment. In this way, the behavior of ants has inspired effective algorithms that can be used in various problem domains.

IV. EXPERIMENTAL STUDIES

The proposed hybrid approach by combining the Voronoi diagram and ACO was tested in a workspace with 32 obstacles. Figure 2a depicts the workspace, while Figure 2b illustrates the Voronoi diagram applied to the same workspace. All codes of the proposed hybrid approach are written in Python programming language. The parameters of ACO used in the experimental studies are given in Table 1.

Table 1. The parameters of ant colony optimization

Parameter	**Value**
Number of ants	20
Number of iterations	50
Evaporation coefficient *(ρ)*	0.3
Initial Pheromone *(τ)*	0.5
Alpha *(α)*	0.5
Beta *(β)*	0.5

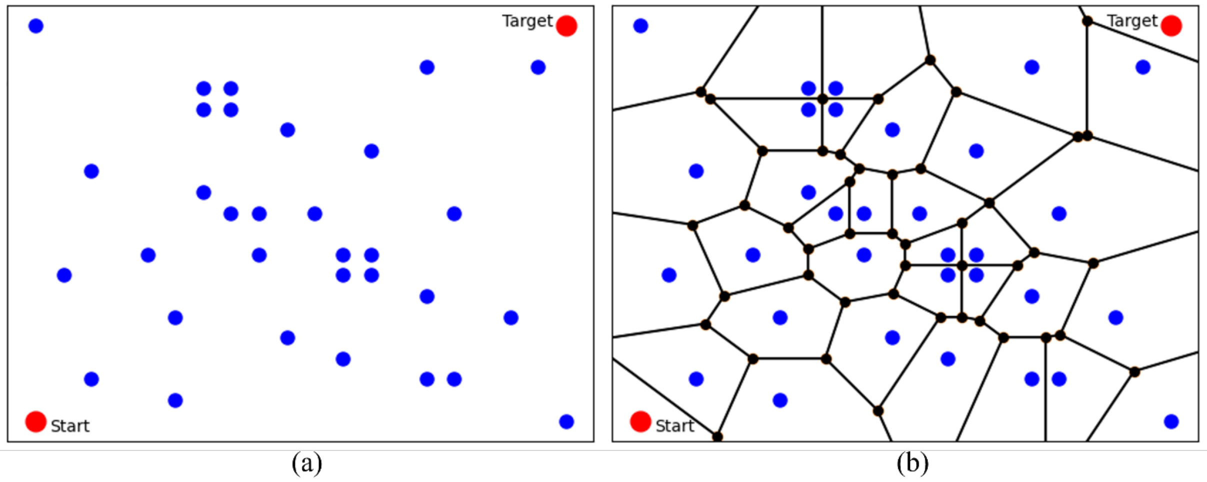

Figure 2. (a) Environment with starting point, target point and obstacles **(b)** Voronoi diagram of the environment

A safe and shortest path, avoiding obstacles as much as possible found by ACO is shown in Figure 3. The mobile robot moves from the nearest vertex to the starting point to the closest vertex to the target. Voronoi lines passing between adjacent obstacles were ignored during path planning since there was no distance for the mobile robot to traverse. These lines are represented by dashed lines in the figure.

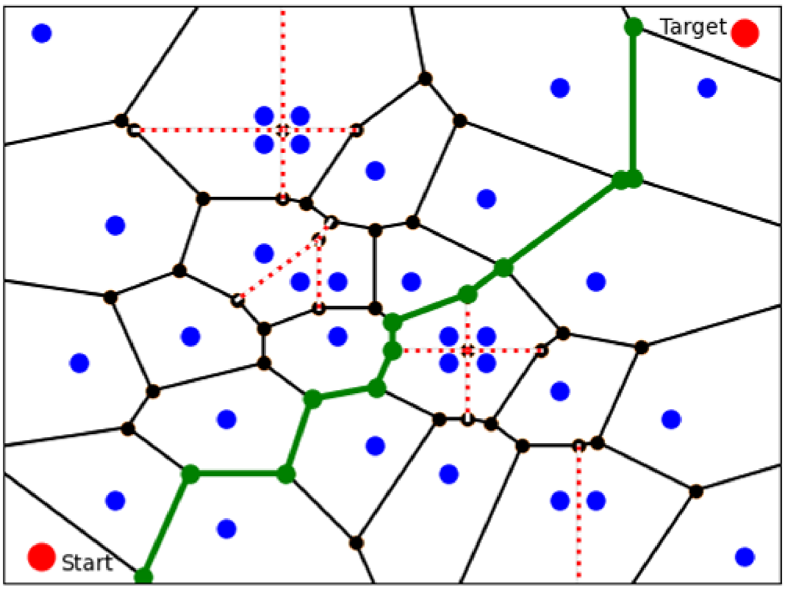

Figure 3. The shortest path using Voronoi diagram and ant colony optimization

The convergence graph of the ant colony optimization is given in Figure 4. As can be seen from the figure, it is understood that the algorithm converges quickly and is effective in solving the problem.

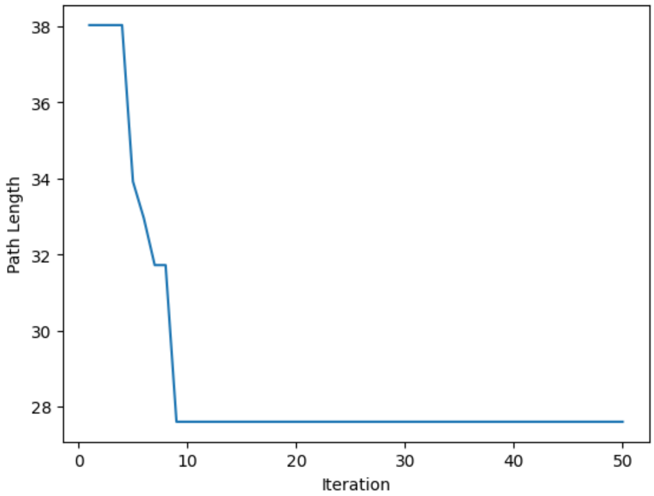

Figure 4. The convergence ant colony optimization

V. CONCLUSIONS

For mobile robots to navigate safely and effectively in a variety of contexts, path planning is a crucial component of autonomous navigation. Effective path planning algorithms are needed to ensure task completion and improve their trajectories. Numerous algorithms are discussed in the literature to address these challenges. Despite improvements, path planning for mobile robots still faces issues, including collision avoidance and handling uncertainty in dynamic situations, which remain active research areas. While these advances are promising, more study has to be done to improve the design of the algorithms in this area, especially with regard to their fast computation speed and robustness in real-world circumstances. As a result, path planning for mobile robots is the cornerstone of autonomous navigation, and therefore path planning for mobile robots continues to be studied to improve the safety and effectiveness of autonomous systems operating in the future.

In this study, a hybrid approach was pursued by combining a Voronoi diagram and an ant colony algorithm. The robot's continuous environment path planning was carried out, as opposed to grid-based mapping. The robot's interaction with obstacles was minimized, and a safe path was planned by using the Voronoi diagram to generate paths that keep the robot as far away from obstacles as possible. Although the Voronoi diagram automatically generated paths that crossed nearby obstacles, these paths were disregarded and not used in the path design. ACO was then employed to find the shortest path among all the paths generated using the Voronoi diagram. According to an experimental study, ACO can be utilized to find the shortest path among the paths generated by the Voronoi diagram that are sufficiently far from obstacles.

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